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From Prediction to Interpretability of Artificial Neural Networks: Application to Senegal's GDP Per Capita.

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Abstract

This article evaluates the predictive capability of ANNs (Artificial Neural Networks) and attempts to interpret their "black box." It provides a detailed analysis of their architecture and explores different interpretability techniques for predictions suited to opaque models—both model-specific and agnostic approaches. The performance analysis of various ANN architectures reveals that the model with 2 hidden layers and 8 nodes remains the most effective. It offers the best balance between accuracy and generalization, with a high-test coefficient of determination ($R^2 = 0.95$) and minimal errors (RMSE = 0.084, MAE = 0.058). The graphical analysis highlights the complex relationships between several economic variables and their impact on GDP per capita. This type of ANN embodies a synthesis of technical sophistication and economic pragmatism, making it ideal for predictive or decision-making analyses in uncertain environments, such as that of Senegal. In summary, the key findings indicate that economic policies should focus on controlling inflation, strengthening productive investments, and ensuring efficient management of public spending. These results thus provide a valuable foundation to guide economic decisions and optimize strategies for economic and social development.

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1. INTRODUCTION

Economic actors, particularly public policymakers, require relevant information on economic activities and outlooks to achieve sustainable economic growth. However, given the complexity and uncertainty of financial and economic systems – driven by frequent changes in economic environments – it remains challenging to make accurate forecasts (Park and Yang, 2022).

In recent years, increasingly sophisticated forecasting methods, such as artificial neural networks (ANNs), have emerged. As Murdocha et al. (2019) note, machine learning models have achieved remarkable success in predicting unobserved data. These authors argue that "*the ability to interpret what a model has learned is receiving growing attention*." Thus, regardless of the country or group of countries considered, the use of these forecasting models by policymakers is both legitimate and prudent for informed economic decision-making.

In Senegal, the current economic situation appears challenging, characterized by a significant budget deficit and substantial public debt. Like most developing countries, Senegal has recorded a chronic budget deficit for several years. An analysis of the past decade's statistics reveals that the ratio of the overall fiscal balance to GDP has deteriorated from -3.96% in 2014 to -9.85% in 2019, reaching -12.30% in 2023 (Directorate of Forecasting and Economic Studies [DPEE], 2025). Public debt has surged from 4,112.9 billion CFA francs in 2014 (42.1% of GDP) to 18,558.91 billion CFA francs in 2023 (99.7% of GDP) (DPEE, 2025). In this context, public policy decisions must rely on accurate forecasts of macroeconomic variables, particularly the key indicator: GDP per capita (GDP/capita).

Given this, it is timely to investigate the best ANN model for predicting Senegal's GDP/capita. This article aims to identify the ANN model that offers the most accurate predictions for Senegal's GDP per capita. The preferred hypothesis posits that a neural network model with two hidden layers is the most effective for this purpose, supported by empirical findings (Eskin et al., 2024).

To achieve this, several interpretability techniques tailored to opaque models. Neural Interpretation Diagram (NID), Garson's Weighting Method, Partial Dependence Plots (PDP) are employed. The predictive accuracy of neural network models is assessed using three performance metrics: the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) (Diakhate and Dieng, 2022).

Few prior studies have employed interpretability-enhanced artificial neural networks (ANNs) to examine the determinants of per capita GDP in Senegal. The originality of this article lies in its integration of interpretability techniques into the macroeconomic modeling of developing countries, using Senegal as a case study. In this regard, the paper offers a novel and specific contribution to the literature on economic forecasting and explainable artificial intelligence (XAI).

The article is structured into five sections. Section 2 reviews the literature. Section 3 outlines the methodology. Section 4 presents and analyzes the forecasting results. Section 5 concludes by discussing economic policy implications.

2. LITERATURE REVIEW ON VISUALIZATION AND INTERPRETABILITY OF NEURAL NETWORKS

For some authors, including Liu and Xu (2023) and Alber et al. (2019), deep neural networks have spurred a revolution in machine learning applications in recent years, becoming indispensable for critical decision-making or predictive processes. This underscores the need to understand and analyze the actions and predictions of various neural network architectures, including the most complex (Alber et al., 2019). Their popularity stems from their applications across diverse fields, including macroeconomics.

However, the most frequent criticism remains their low interpretability as "black-box" models (Ponomareva and Caenazzo, 2019). Nevertheless, available literature has sought to improve the understanding and visualization of neural networks, primarily focusing on image classification. Understanding, visualizing, and explaining deep neural networks are thus essential for better utilization. Apley and Zhu (2016) argue that the lack of interpretability or transparency is the primary limitation of black-box supervised learning models. Several visualization tools for general black-box models have been proposed.

Partial dependence (PD) plots, the most widespread visualization approach, were later supplemented by individual conditional expectation (ICE) plots (Goldstein et al., 2014). Accumulated local effects (ALE) plots (Apley and Zhu, 2016) were introduced as an alternative to PD and ICE plots, which were criticized for their invalidity with correlated features (Grömping, 2020). PDPs help visualize the average partial relationship between predicted responses and one or more features.

Interpreting statistical and machine learning models requires analyzing variable importance summaries, interaction measures, and partial dependence plots. Several authors, including Štrumbelj and Kononenko (2011), Doshi-Velez and Kim (2017), Ghorbani et al. (2017), Alvarez-Melis and Jaakkola (2018), and, Alber et al. (2019), have addressed interpretability challenges and proposed definitions and interpretation methods.

Montavon, Samek and Müller (2017) tackle the problem of interpreting deep neural network models and explaining their predictions. Drawing on a tutorial and a representative set of methods, they provide theory, recommendations, and tips for more effective use of layer-wise relevance propagation (LRP) on real-world data. Ponomareva and Caenazzo (2019) estimated credit risk for a credit card portfolio using deep neural networks. Their results reveal that "*relevance analysis, sensitivity, and neural activity*" can enhance "*the interpretability of a neural network in financial modeling*."

More recently, Alan Inglis et al. (2021) proposed new visualization techniques applicable to regression and supervised classification parameters, such as heatmaps and graphical displays that facilitate model summary exploration.

Several studies have explored explainable AI (XAI) models, particularly those attempting to explain deep neural network architectures. Various XAI approaches exist, including local and hybrid interpretability models and global interpretation methods. For Saleem et al. (2022), "*global* *interpretation methods have emerged as primary explainability methods because they can explain each feature and the model's structure*." Global interpretation methods provide a comprehensive explanation of AI model behavior.

Using a nonlinear autoregressive neural network, Jin et al. (2025) achieved accurate and stable predictions, with low forecast errors for the trading volume observed on thermal coal futures traded on the Zhengzhou Commodity Exchange in China.

However, some deep learning approaches can deliver high-frequency, fine-grained forecasts and effective results, "*but their interpretability remains controversial*" (Wang et al., 2022). Thus, simultaneously achieving performance and interpretability is, according to Wang et al. (2022), "*a universal concern and an urgent unresolved problem*." In this vein, these authors proposed EcoForecast, an interpretable data-driven approach for short-term macroeconomic forecasting based on the N-BEATS neural network (Neural Basis Expansion Analysis for Interpretable Time Series Forecasting).

Applied to China's real macroeconomic data from 1992 to 2022, EcoForecast demonstrated "*high stability across different sequential learning scenarios*" with high-precision performance"*lower prediction error and variance, tolerance to reduced input samples, and robustness across prediction domains*" (Wang et al., 2022). Experimental results showed that EcoForecast improved accuracy by up to 3.94 times compared to traditional BVAR (Bayesian Vector Autoregression). In robustness testing, EcoForecast used only a quarter of the data to achieve forecast errors 2.51 times lower than BVAR, while also improving the Purchasing Managers' Index (PMI) forecast accuracy by 2.38 times and national electricity production forecasts by 1.45 times (Wang et al., 2022).

The empirical work of Jin and Xu (2024) revealed the strong potential of Gaussian process regression with Bayesian optimizations for modeling and forecasting complex commodity price time series for market participants.

Other proposals have been made for achieving intelligent economic decision-making. Park and Yang (2022) proposed two approaches for better economic forecasting and decision-making. The first is "*a deep learning model based on a long short-term memory (LSTM) network architecture*," which forecasts economic growth rates and crises by "*capturing sequential dependencies within the economic cycle*." The second is an interpretable machine learning model derived from "*economic growth and crisis models through effective use of the eXplainable AI (XAI) framework*."

The LSTM model outperformed traditional predictive models for major G20 countries from 1990 to 2019, particularly in emerging economies (Park and Yang, 2022). Their results show that private debt in developed economies and public debt in emerging economies are key factors limiting future economic growth. Regarding COVID-19's economic impact, their findings also indicated that sharp interest rate declines and rising public debt increased the likelihood of future crises in some emerging countries.

Jin and Xu (2025), using PC algorithms and the Linear Non-Gaussian Acyclic Model (LiNGAM) for directed acyclic graph (DAG) inference, found a complex dynamic in the adjustment processes of monthly commercial real estate price indices in 10 major Chinese cities following shocks.

Xu (2020), evaluating thirty individual time series models and ten combined forecasts based on six pruning strategies, used the unconstrained least squares method, without a constant, to estimate the combined weights of the individual models without pruning. The result obtained was a model recalibration frequency of at least one month.

Liu and Xu (2023) reviewed recent advances in interpretable neural networks, presenting various application scenarios for deep interpretable neural networks (DINs) and discussing existing challenges and future directions. These authors distinguish two DIN methods: model decomposition neural networks, which pre-design an interpretable network structure, and semantic DINs, which assign post-hoc interpretability to a black-box network structure.

Ultimately, the results of various studies confirm the relevance of ANNs for forecasting and interpreting macroeconomic variables. In this context, using ANNs to predict Senegal's GDP/capita is justified.

3. METHODOLOGY

3.1 Data and Variables

The model is based on a Keynesian approach, where GDP/capita depends on components of aggregate demand, including domestic spending (Tammar, 2021), government expenditure (Aschauer, 1989), and gross fixed capital formation (GFCF, investment) (Ntamwiza et al., 2022). Control variables influencing GDP/capita include trade openness (Rodriguez and Rodrik, 2001), inflation (Arawatari et al., 2018), and population growth rate (Mankiw, Romer and Weil, 1992).

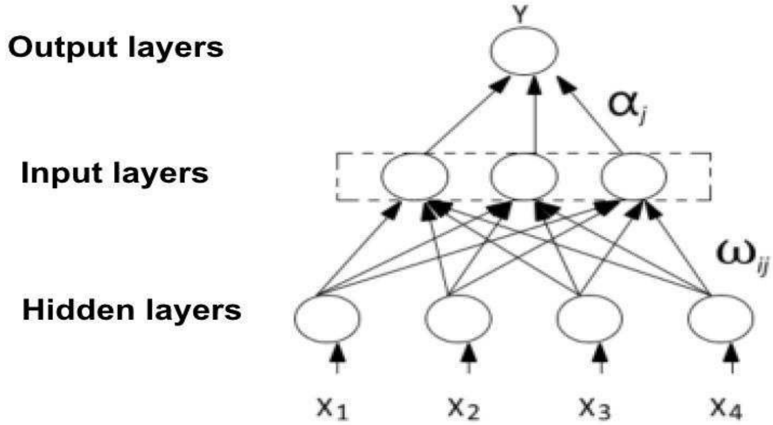
These variables are defined by the World Bank Indicators (WDI). The data, spanning 63 years (1960–2023), were extracted from the WDI database using the R package WDI

3.2 ANN Architecture and Training

3.2.1 Architecture

The methodology is based on ANNs, inspired by the human brain and introduced by McCulloch and Pitts (1943). Unlike parametric methods, ANNs offer a nonlinear, data-driven adaptive approach rather than relying on explicit probabilistic models. Among various architectures, the feed-forward network was selected for its unidirectional structure (input → output without feedback loops). These models are particularly effective for analyzing complex, non-explicit relationships between variables, as illustrated in Figure 1.

Figure 1: Schematic of a Feed-Forward Neural Network



Source: Authors

Figure 1: Schematic representation of a feedforward neural network. The architecture illustrates the flow of information from the input variables through weighted connections to the intermediate layer, and finally via weights to the output node.

X = (x_1, x_2, x_3, x_4) are the inputs to neuron i
Y = Output variable
W_{ij} = Weight of neuron i
α_i= Bias

The bias α_i regulates the net input of the activation function based on whether it is positive or negative. A negative weight is inhibitory, reducing the net contribution, while a positive weight is excitatory, increasing it. The feed-forward model equation is:

$$Y_t = \omega_0 + \sum_{i=1}^{I} \omega_i \,.\, \varphi\left(\alpha_i \;+ \sum_{j=1}^{J} \Omega_{ji} \,.\, x_{t-j}\right) + \varepsilon_t \qquad (1)$$

Where ω_i and $\Omega_{ji}$are the parameters of the model and represent respectively the weight of the intermediate, nodes connected to the output node. The matrix of parameters connecting the input nodes to the intermediate nodes. are the biases connecting the last hidden layer and the response variable of the model. $i = 0,1,2, \dots, I$ and $j = 0,1,2, \dots J$ with I being the number of independent input nodes or variables. J, represents the number of nodes at the intermediate layer. X represents the input values. Each input value is connected to a weight which will affect the output variable. is the activation function given by the following formula:

$$\varphi(x) = \frac{1}{1 + e^{-x}} \qquad (2)$$

This function is applied to the last hidden layer to obtain the output layer (Shengkun Xie et al., 2020).

3.2.2 Training

In the model, GDP/capita is the dependent variable. The dataset is split into two parts: a training set (80% of the data) for analyzing variable relationships and a test set (20%) for evaluating model performance.

Several configurations of fully connected feed-forward neural networks were tested by adjusting hidden layer dimensions and neuron counts. Only a two-hidden-layer configuration was retained due to superior performance. For each configuration, nested 10-fold cross-validation was employed. This involves an inner loop for performance optimization and an outer loop for generalization error evaluation, which is done by averaging performance over several divisions of the test set.

In addition, the number of samples in the training set for the first loop was varied from 1 to 35. For each value in this set, 100 samples were drawn and the remainder reserved for the test set. This cross-validation approach not only provides a reliable assessment of the model's performance on each of the 3500 training data sets, but also prevents potential biases. The highest performances in terms of accuracy across all training trials are then recorded and evaluated. In the following, the interoperability methods used in this article will be presented.

3.3 Model Evaluation

The presentation and analysis of forecast results will take place in three stages. First, the performance of the results will be analyzed in terms of forecast accuracy. Next, the forecast error graph will be analyzed. Finally, an overall interpretation of the results of the ANN forecast of Senegal's GDP/capita will be proposed.

3.3.1 Forecast Accuracy

There are several alternative performance measures such as mean absolute error (MAE) and Root mean squared error (RMSE), which can facilitate more robust comparisons between different models or target variables. Using these performance measures, Xu and Zhang (2023) demonstrated the relevance of the nonlinear autoregressive neural network model for forecasting the prices of the new energy index in mainland China.

Table I: Forecast Results

Number of hidden layers	**Number of de nods**	**R^2**		**RMSE**		**MAE**	
		Training	Testing	Training	Testing	Training	Testing
3	10	0.982	0.935	0.0506	0.096	0.041	0.071
2	8	0.979	0.950	0.0550	0.084	0.046	0.058
1	8	0.989	0.858	0.0404	0.155	0.031	0.128
1	4	0.981	0.904	0.052	0.121	0.052	0.099

Source: Authors

Table I: A performance comparison of neural network architectures for predicting Senegal's per capita GDP reveals that the model with two hidden layers and 8 nodes per layer achieves the highest test R^2 (0.950) while maintaining low error metrics (RMSE = 0.084, MAE = 0.058.

Results in Table I show that models with more than one hidden layer perform best. High R^2 values (~98% training, ~95% testing) indicate strong correlations between predicted and observed GDP/capita, with independent variables explaining over 90% of response variable forecasts.

The 2-layer, 8-node architecture achieves the best results (R^2 = 95%, RMSE = 8.4%, MAE = 5.8%).The 1-layer, 8-node model (Figure 7c) shows overfitting, excelling in training but generalizing poorly. The 1-layer, 4-node model (Figure 7d) is undersized, with higher test errors. The 3-layer, 10-node model (Figure 7a) performs well, but the added layer offers no significant gains.

Using the optimal architecture (2 hidden layers, 8 neurons per layer; Table I), we applied interpretability techniques such as NID, Garson's weighting, PDP, and the Partial Derivatives Method to assess model behavior.

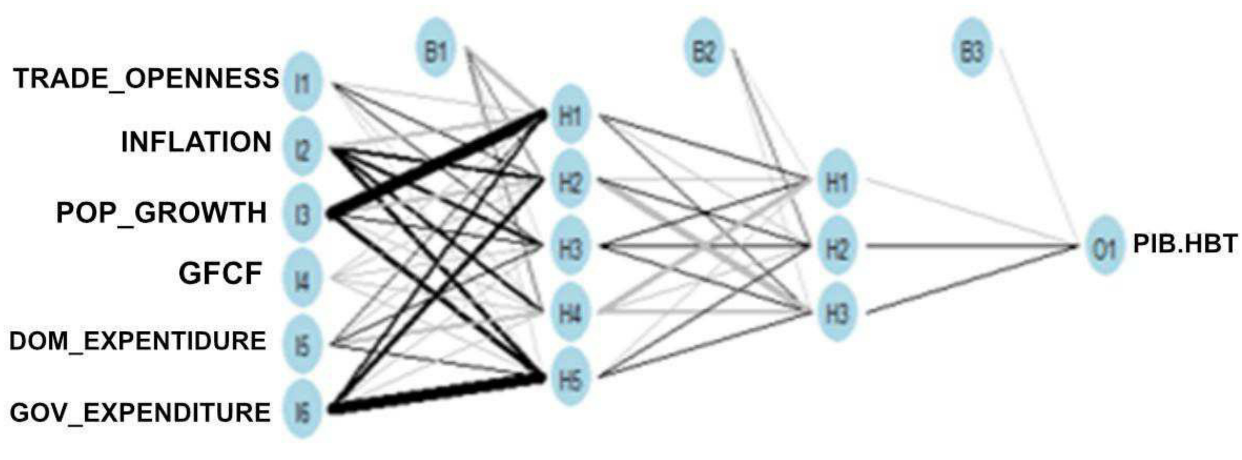
4. RESULTS AND DISCUSSION

4.1 Model Interpretability

4.1.1 Neural Interpretation Diagram (NID)

This global interpretation method defines feature importance as the increase in prediction error after permuting variable values. A variable is important if permutation degrades model performance.

Figure 2: Neural Interpretation Diagram



Source: Authors

Figure 2: Architecture of the Neural Network Model for Economic Prediction. The diagram illustrates a Multi-Layer Perceptron (MLP) designed to estimate Gross Domestic Product per capita (PIB.HBT). The network consists of an input layer with six features, two hidden layers including bias units (B1,B2,B3), and a single output node. The thickness of the connecting lines represents the magnitude of the synaptic weights between neurons.

Figure 2 shows a neural model characterizing the relationships between macroeconomic variables. Connection weights, similar to regression coefficients, describe these relationships. Two hidden layers capture non-linearities, while node reduction simplifies the calculation, adapted to often noisy or incomplete economic data, without losing precision.

Connection thickness indicates contribution importance, and color (black for positive, gray for negative) shows direction. Weights eliminate irrelevant variables for GDP/capita and reinforce strongly correlated ones. For example, input nodes I1 (trade openness) and I4 (GFCF) have negative weights, suggesting adverse effects on GDP/capita. Conversely, I2 (inflation), I3 (government spending), I5 (population growth), and I6 (domestic spending) have positive weights.

Biases (B1–B4) act as intercepts. Final connections reveal that inflation, FBCF, and population growth most influence GDP/capita. Government spending, strongly linked to hidden layers, appears to directly stimulate growth. This architecture highlights key dynamics between economic variables and their impact on GDP/capita.

4.1.2 Garson's Weighting Method

This method evaluates variable importance in neural networks. Olden's algorithm identifies all connection weights between each feature and the response variable, calculating relative importance. Unlike Olden's, Garson's method indicates whether relationships are positive or negative. The Garson statistic is:

$$\boldsymbol{\psi_{ik}} = \frac{\sum_{j=1}^{L}((\omega_{ji}/\sum_{r=1}^{N}\omega_{rj})v_{jk})}{\sum_{i=1}^{N}(\sum_{j=1}^{L}((\omega_{ji}/\sum_{r=1}^{N}\omega_{rj})v_{jk})} \qquad (\mathbf{3})$$

Where ψ_{ik} represents the percentage impact of the input variables x_i on the output y_k, relative to the remainder of the input variables. $\sum_{r=1}^{N}\omega_{rj}$ denotes the sum of the connection weights between the input neurons N and the hidden neuron j . ω_{ji} represents the connection weights between the input neuron i and the hidden neuron j. v_{jk} remains the connection weights between the hidden neuron j and the output neuron k for each of the network's hidden neurons. It is given by:

$$\omega_{ji} = \frac{\sum_{k-1}^{n}((X_{ik} - \bar{X}_i)(Y_{ik} - \bar{Y}_i))}{\sqrt{\sum_{k-1}^{n}(X_{ik} - \bar{X}_i)^2 \sum_{k-1}^{n}(Y_{ik} - \bar{Y}_i)^2}} \qquad (\mathbf{4})$$

The relative importance of each input parameter is given in Table I below.

Table II: Variable Importance According to Garson.

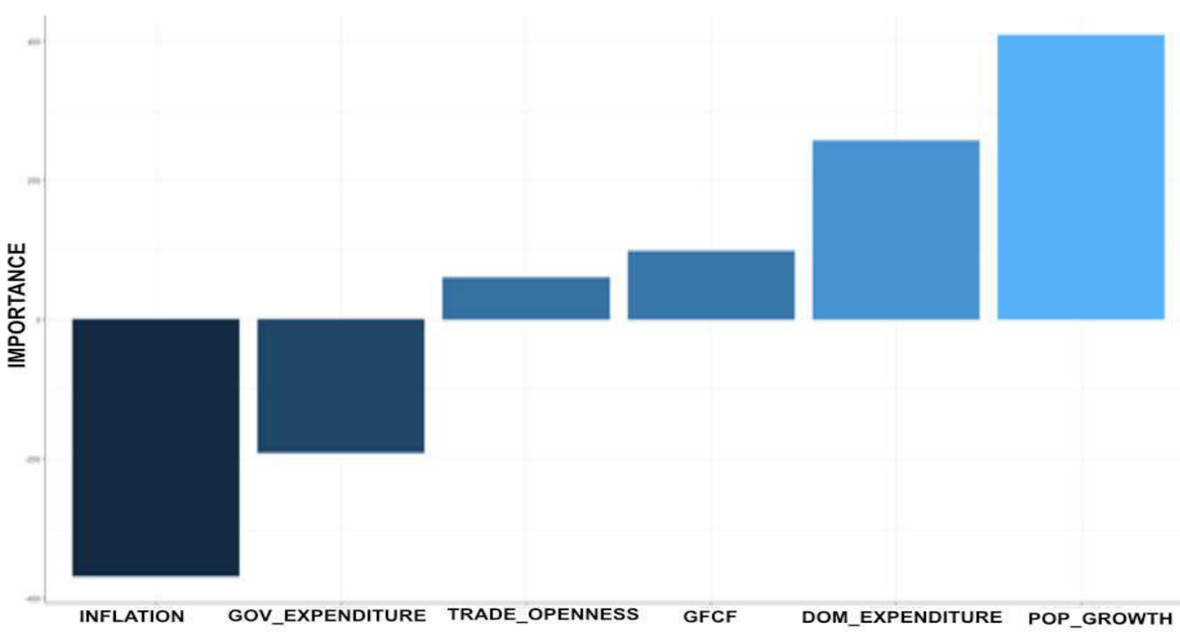
Importance	Variables
-367.99	INFLATION
-191.07	GOV_EXPENDITURE
60.60	TRADE_OPENNESS
98.36	GFCF
256.40	DOMESTIC_SPENDING
408.53	POPULATION_GROWTH_RATE

Source: Authors

Table II: Variable importance rankings according to Garson's algorithm for the selected two-hidden-layer neural network model predicting per capita GDP in Senegal. Positive values indicate a direct relationship with per capita GDP, while negative values denote an inverse relationship. Population growth rate emerges as the dominant driver.

Results show that inflation and population growth have the strongest negative and positive relationships with GDP/capita, respectively Adu-Gyamfi et al. (2020) - Maestas et al. (2023). Trade openness has negligible importance, while GFCF has a marginal but contextually insignificant effect.

Figure 3: Garson's Graph



Source: Authors

Figure 3: Neural network variable importance using modified Garson's algorithm. The plot summarizes the connection weights to determine the relative contribution of each feature. The results highlight the contrast between growth-promoting factors (light blue) and inhibitory factors (dark blue).

The figure illustrates variable importance in predicting Senegal's GDP/capita. Population growth is the most influential, with a strongly positive effect. Domestic spending and GFCF also significantly impact growth, aligning with Barro (1990). Government spending has a negative effect, while inflation is even more detrimental. Trade openness has a modest positive impact (Koutima-Banzouzi, 2023).

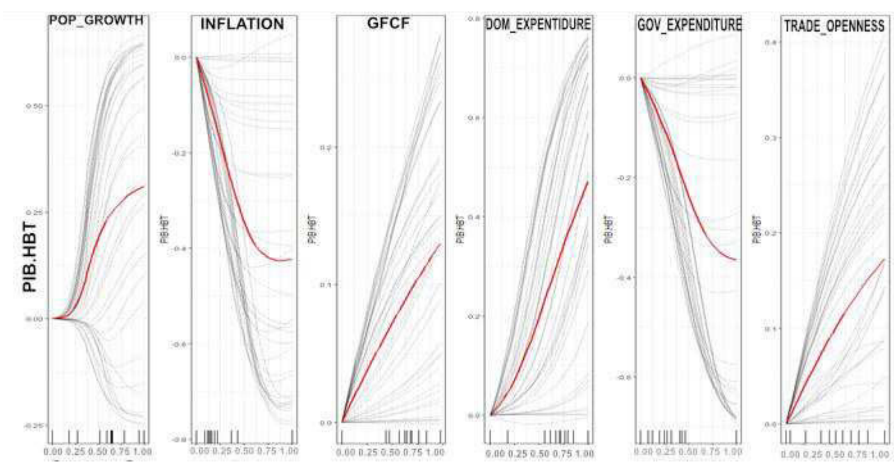
4.1.3. Partial Dependence Plots (PDP)

PDPs analyze the marginal effect of a macroeconomic variable on GDP/capita, offering a global view by calculating average relationships. Derived from ICE curves, PDPs reveal individual deviations from average trends.

$$\widehat{PDP}_j(x_j) = \frac{1}{n}\sum_{i=1}^{n} \hat{f}\left(x_j, x_{-j}^{(i)}\right) \qquad (5)$$

Where n is the number of observations used, the $x_{-j}^{(i)}$ represent the actual attribute values of the set of uninteresting values (the black lines in figure X). $\widehat{PDP}_j$ belongs to the interval $[\min(x_j), max(x_j)]$ with $x_j = \left(x_j^{(i)}, \ldots, x_j^{(nj)}\right)$.

Figure 4: Partial Dependence and Individual Conditional Expectation Plots



Source: Authors

Figure 4: Partial Dependence (PDP) and Individual Conditional Expectation (ICE) plots. The graphs visualize the marginal effect of each feature on the predicted GDP per capita (PIB.HBT), holding other variables constant. The thick red line represents the average effect (PDP), while the thin grey lines depict the relationship for individual observations (ICE), highlighting potential heterogeneity in the data. The rug marks along the x-axis indicate the distribution of the observed data points.

The figure shows the impact of explanatory variables on GDP/capita using PDPs. Each panel displays GDP/capita predictions against a specific variable, with average trends in red and individual trajectories in black.

For population growth, the PDP indicates a positive correlation with GDP/capita. Predictions rise gradually by 0.0125 as growth increases, with a sharp uptick beyond 20%. This suggests nonlinearity and potential interactions with other variables.

GFCF and domestic spending are positively associated with GDP/capita (Ntamwiza et al., 2022; Carvalho et al., 2021, respectively). A GFCF increase leads to a near-linear GDP/capita rise, implying investment-supportive policies could directly boost growth. Domestic spending also drives GDP/capita, though less markedly than GFCF.

Government spending negatively affects GDP, suggesting excessive or poorly allocated public expenditure may hinder growth. This aligns with Blanchard and Leigh (2013), who found fiscal austerity, affected negatively the GDP. This confirms the results obtained from the garson's analysis.

Inflation exerts a strongly negative effect, as rising prices reduce purchasing power and create economic uncertainty. The PDP shows GDP/capita declines by 0.4 with inflation before stabilizing beyond 75%. This corroborates (Jordà et al. 2024), who argue persistent inflation above 5% discourages private investment and reduces long-term GDP growth.

Trade openness positively correlates with GDP/capita, highlighting globalization benefits. However, the relationship is nonlinear. In Sub-Saharan Africa, trade expansion drives growth, with inter-regional trade contributing 1.9% and intra-regional trade 0.6%, highlighting its greater influence (Calderon et al. 2020).

4.1.4. Sensitivity

This method examines explanatory variable importance by analyzing response variable sensitivity. Figure 5 shows the mean effect of input variables on GDP/capita (x-axis) and combined variance impact (y-axis).

Figure 5: Sensitivity Analysis

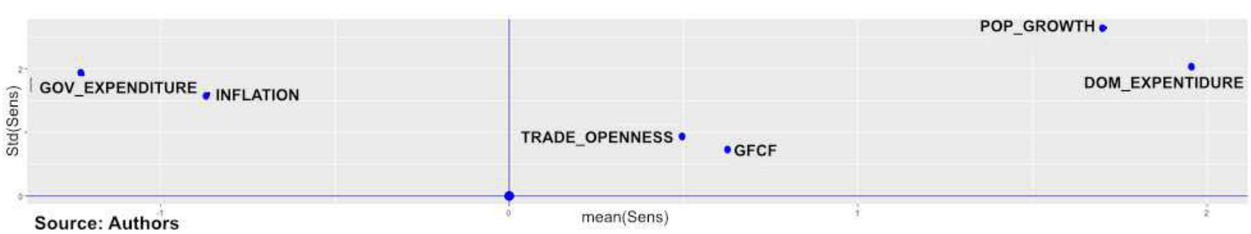


Figure 5: Mean vs. Standard Deviation of variable sensitivity. The plot categorizes the macroeconomic determinants by their average impact on the target variable (x-axis) and the heterogeneity of that impact across the data space (y-axis).

Population growth and domestic spending are the most influential factors, with high mean impact and low variability, indicating stable roles in economic dynamics. They show a non-linear but positive relationship with the response variable. This result corroborates that of Pizarroso et al. (2022).

Inflation and government spending show significant mean and variance, suggesting nonlinear, context-dependent relationships with GDP/capita. Both have negative effects, confirming earlier findings. This matches Adu-Gyamfi et al. (2020) on inflation's negative GDP impact but contradicts Tammar (2021) on government spending's effect on GDP per capita.

GFCF and trade openness exhibit moderate impacts, implying long-term rather than immediate economic influence. Investment is a key growth factor, and trade openness amplifies its positive impact, as shown by John Boamah et al. (2018).

These results underscore the need to stabilize inflation, optimize public spending allocation, and promote strategic investments for sustainable growth.

4.2 Forecast Validation

4.2.1 Forecast Error Analysis

Error analysis (Figure 6) shows RMSE and MAE decline as observations increase, indicating ANN model improvement. ANN.532 (blue) and ANN.53 (red) perform best, with lower errors and greater stability. ANN.4 (orange) and ANN.8 (green) are less accurate.

Figure 6: Forecast Error Curve

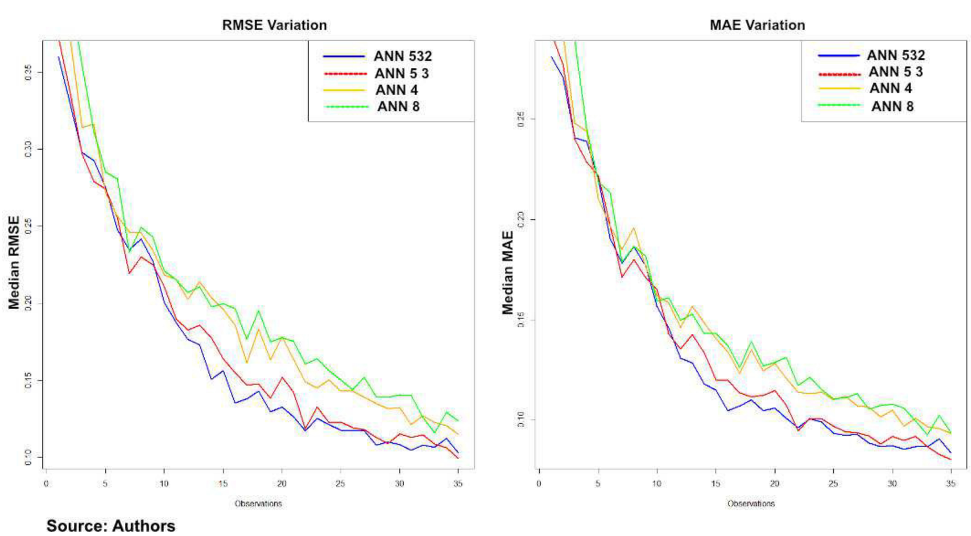


Figure 6: Convergence analysis of ANN architectures. Comparison of RMSE (left) and MAE (right) for neural networks with varying hidden layer configurations. The "ANN 532" model achieves the lowest median error, indicating superior predictive performance.

Errors are high and unstable initially but stabilize after 30 observations, demonstrating strong learning and generalization capabilities. ANN.532 is the most reliable for precise forecasts, while ANN.4 and ANN.8 require adjustments.

4.2.2 Observed vs Predicted

The optimal model is the 2-layer, 8-node network, balancing accuracy and avoiding over-/under fitting. It closely mirrors observed values, explaining the 95% R^2.

Figure 7: Observed vs. Predicted Variables

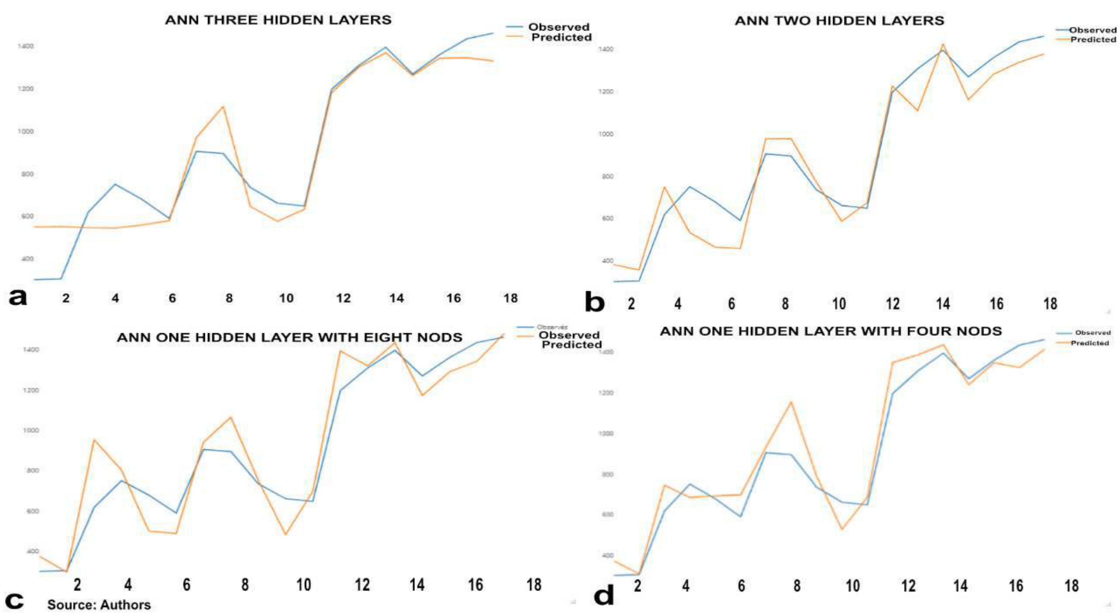


Figure 7: Visual assessment of model fit for different ANN configurations. The architecture with two hidden layers (top right) demonstrates the best generalization with a stable fit, whereas the single hidden layer with eight nodes (bottom left) exhibits high variance and instability, indicative of overfitting. The three-layer models (top left, bottom right) show a lag in capturing initial volatility but align well with the final trend.

The experimental results indicate that the intermediate architecture with two hidden layers consistently outperforms both the shallow (one-layer) and deeper (three-layer) models, demonstrating superior stability and convergence properties. Exclusive reliance on the training R^2 values reported in Table I would have erroneously favored the single-layer model with eight nodes, despite its markedly inferior real-world performance. Figure 7's learning curves reveal the severe overfitting and instability of this configuration, underscoring the limitation of training metrics in isolation. A combined analysis of Table I and Figure 7 provides conclusive evidence supporting the selection of the two-hidden-layer architecture with eight nodes per layer. This model exhibits smooth convergence, high reliability, and excellent generalization, as confirmed by both its training trajectory and independent test-set metrics.

4.3. Global Interpretability

Sensitivity analysis reveals key influencers government spending, inflation, trade openness, and GFCF. High-dispersion variables exhibit nonlinear relationships with GDP/capita. Inflation's strong negative impact underscores the need for stabilization policies.

Trade openness and investment positively affect growth, but policies must mitigate external dependency risks. Government spending's efficacy depends on allocation efficiency, highlighting the need for rigorous fiscal management.

Inflation remains a key risk to monitor in Senegal to avoid economic imbalances. However, its negative effect can be offset by robust trade activity.

Variable importance analysis (Table II) confirms population growth and domestic spending as top positive drivers. Inflation remains the most detrimental factor, emphasizing price stability as a policy priority.

5. CONCLUSION

This article evaluates ANNs' predictive capacity and interprets their "black box." After reviewing ANN evolution and analyzing their architecture, it explores interpretability techniques for opaque models, distinguishing model-specific (NID, partial derivatives, Garson) from agnostic (PDP) methods.

Performance analysis reveals the 2-layer, 8-node model as optimal, offering the best precision generalization trade-off ($R^2 = 0.95$, RMSE = 0.084, MAE = 0.058).

Graphical analysis highlights complex economic variable relationships and their GDP/capita impact. The ANN model delivers relatively accurate predictions, though some observed-predicted gaps remain, suggesting potential hyper parameter tuning or data augmentation. This ANN balances technical sophistication and economic pragmatism, ideal for predictive/decision-making analyses in uncertain environments like Senegal's.

Forecasting and interpreting Senegal's GDP/capita demonstrates that economic policies should prioritize inflation control, productive investment, and efficient public spending. Trade openness should be encouraged within a framework shielding against external volatility.

Demographic growth, while beneficial, requires infrastructure and education investments to ensure long-term positive impacts. These findings provide a valuable foundation for guiding economic decisions and optimizing socioeconomic development strategies.

The unavailability of comprehensive institutional data covering the entire observation period constitutes a limitation of this work. Indeed, empirical studies including that of Acemoglu et al. (2001) emphasize the decisive role of institutional frameworks in the long-term dynamics of GDP per capita. In a future research perspective, the availability of such data would make it possible to account for the institutional effect on the growth trajectory of GDP per capita.

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